Periodicals of Engineering and Natural Sciences ISSN 2303-4521
Vol. 8, No. 1, January 2020, pp.6-21

Industry 4.0 challenges to IE paradigms: A pilot study in materials handling

Gizem Mullaoğlu[1], Sencer Yeralan[2]
[1] Department of Industrial Engineering, Yaşar University, Bornova, 35100, İzmir, Turkey
[2] Agricultural and Biological Engineering Department, University of Florida, Gainesville, FL 32611, USA

ABSTRACT

Industrial engineering practices are expected to be affected by, and most likely adapt to, the new paradigms of Industry 4.0. Early indications in practice, as well as extrapolations from the current technology trends, point toward a few fundamental features. Among these are further integration, leaner and hence more agile practices, and the use of real-time data. The final objective is to reduce complexity while striving for real-time supply- and production-chain optimization. We argue that the optimization of highly integrated production systems cannot be sought by simply aggregating the known operations management tools of industrial engineering. Specifically, we present evidence, gleaned from a recent industrial project, that indicates how as the systems become more integrated, the concept of operations optimization needs to be revisited. Our work has two distinct contributions to the literature. We develop and present a state-of-the-art optimization model for a joint materials handling, inventory, and scheduling model. The model incorporates aspects of the knapsack, bin packing, vehicle routing, and inventory control formulations. Further, we show that simply collecting existing industrial engineering models into larger aggregations, albeit in line with the current best practices of our profession, will not necessarily suffice to completely fulfill the ambitions of Industry 4.0.

Keywords: Industry 4.0, materials handling, kanban system, aggregate model, future trends

Corresponding Author:

Gizem Mullaoğlu,
Department of Industrial Engineering,
Yaşar University,
Bornova, 35100, İzmir, Turkey
E-mail: gizem.mullaoglu@yasar.edu.tr

1. Industry 4.0

Industry 4.0[1] is considered as 'a collective term for technologies and concepts of value chain organization which draws together Cyber-Physical Systems (CPS), the Internet of Things (IoT), and the Internet of Services (IoS)'. Some view it to be a logical extension of lean production or lean automation. CPS integrates not only production software and hardware (machines) but also the work pieces through the use of contemporary Internet and Communication Technologies (ICT). The approach entails duplicating the manufacturing environment in a virtual world where optimal decentralized decisions are made using real-time data [1, 2, 3]. The components are envisioned to have what may be viewed as a level of rudimentary consciousness. Besides decision making, the collective is to predict failures, perform self-configuration, and

[1] Although the original effort is named Industrie 4.0, the concept is viewed slightly differently in the United States, where it is known as Industry 4.0. The differences are not relevant to our work, and hence, we use the term as it is preferred by the management of the manufacturing plant where the study was conducted.

organically adapt to changes. It is noteworthy that this collective concurrent view manufacturing systems is shared by other newly emerging management paradigms, e.g. "holistic integration" [4].

Baur and Wee [5] list *Industry 4.0 Levers* classified under *Value Drivers*, of which the two, *Inventory* and *Quality* are close to operations management activities of traditional industrial engineering. Breunig et al. [6] provide a road-map for those companies who would like to implement Industry 4.0. It is suggested that companies focus initially on a limited number of aspects, among which 'real-time supply-chain optimization' seems to be a reasonable first target.

The project was instigated when the company decided to investigate the potential of Industry 4.0 by focusing on the levers *Batch Size* and *Real-Time Supply Chain Optimization* under the value driver *Inventory* [5]. The objective was to implement real-time optimization in a lean production manner by use of advanced optimization software. The software is be run parallel to production using real-time data, thereby implementing the virtual world aspect of Industry 4.0. The pilot project regards the materials handling system, which had been set up following lean manufacturing principles as a Kanban system. Kanban, being a rather intuitive and natural control mechanism, is a good starting point towards decentralized decision making.

Applying Industry 4.0 paradigms implies a few things: the system follows lean manufacturing principles, real-time information is utilized at all levels of decision making, and decisions are made using optimization techniques. The initial request from industry was to use operations research techniques, specifically, mixed-integer programming, in a real-time manner running concurrently with production. That is, real-time information is to be used to make operational materials handling decisions. This is precisely what has been prescribed by Industry 4.0 proponents [1, 2, 3].

It is the contribution of this paper that simply elevating the level of integration and implementing optimization techniques in a lean manufacturing environment does not guarantee the desired Industry 4.0 outcomes. This is a most concerning finding for industrial engineering, as it implies that if Industry 4.0 is to be adopted, much conceptual work is needed in the clarification, re-definition, and re-formulation of the fundamental elements of manufacturing systems. In short, as we will expatiate in the remainder of the paper, taking a lean manufacturing system and applying mathematical programming techniques to optimize various operational aspects in a largely integrated manner is not necessarily sufficient.

1.1. Scope, purpose, and contribution

The study attempts to satisfy industry demand of implementing Industry 4.0 by bringing together the standard models of operations research to construct a combined optimization tool. Any type of sequential optimization of the sub problems is clearly against the spirit or philosophy of Industry 4.0. The combined optimization tool is to feed off of real-time data, and achieve the levels of efficiencies promised by Industry 4.0 through a high level of integration[2].

The study was designed to be the first leg of this pilot project, which attempts to clarify the elements, and investigates the feasibility of achieving the desired results. As a starting point, before a full-scale solution is attempted, a simplified setting was chosen as the domain of the pilot study. The materials handling system model was simplified by reducing the number of parts, the number of stations, the number of transports, etc. If it is found promising, a full-scale implementation was to be undertaken, most likely by refining the solution procedure by heuristics. However, if the desired results cannot be achieved even in this simplified setting, then the study would serve as a uncluttered counterexample to rethink industrial engineering approaches to any future implementation of Industry 4.0.

The details of the research design are given as a flowchart in Fig. 1. As it is describe in the remainder of the paper, simply aggregating the known industrial engineering practices into a large combined model is not guaranteed to give the desired Industry 4.0 outcomes. Although this finding is somewhat discouraging, it also

[2] As we were told by our industry partner, "No islands of optimization, we seek total holistic optimization!"

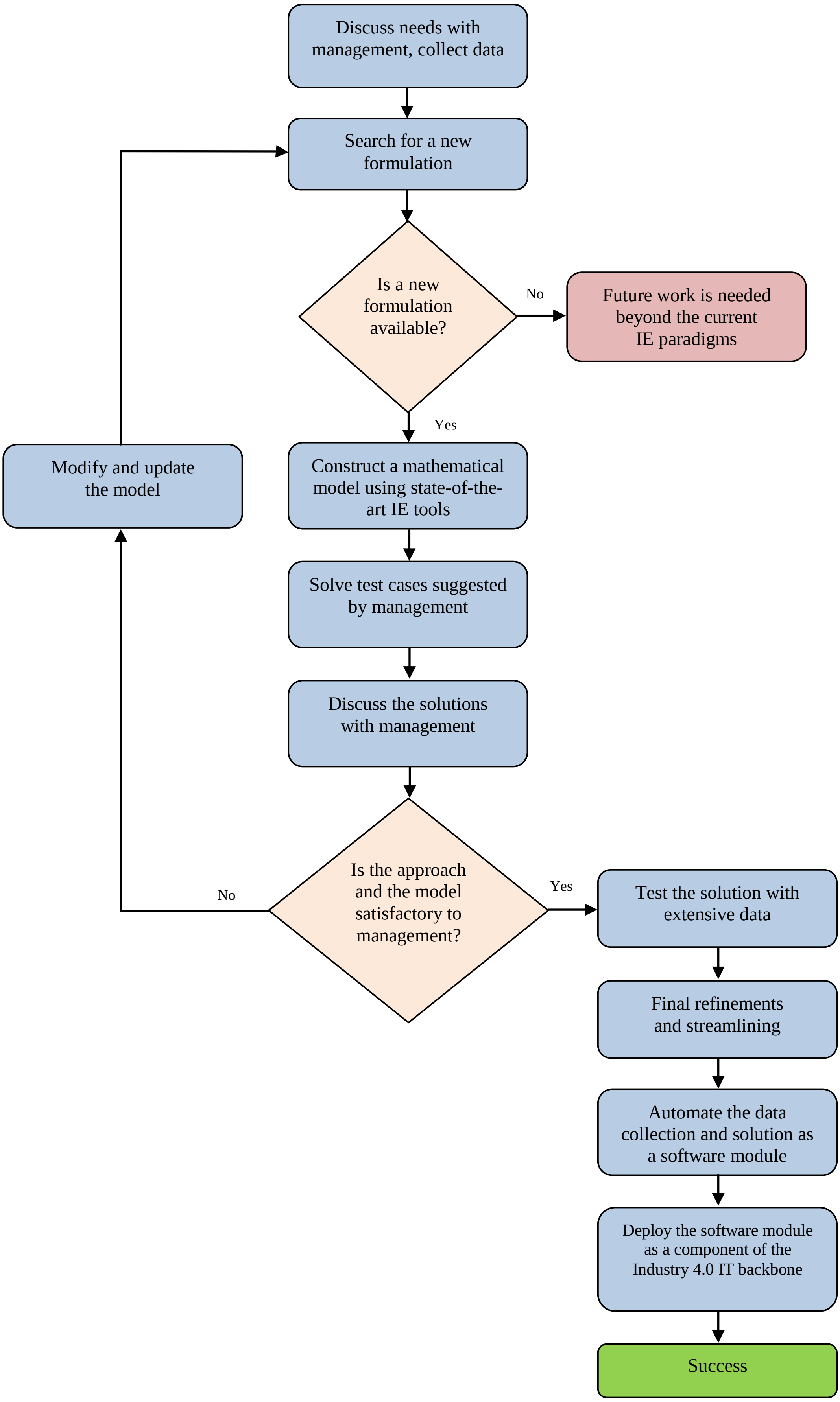

Figure 1. Flowchart of design procedure (see text for the discussion on why the process is guaranteed to terminate)

comes with a message of opportunity. It indicates that, rather than a stagnated field of inquiry, there are many new opportunities to extend industrial engineering models and approaches.

In the following sections, we describe the setting in which the pilot study was conducted. The setting is embedded in materials handling and Kanban systems. Accordingly, a brief review of these topics is given. Afterwards, we develop a combined model that has elements of materials handling, assignment, bin packing, and inventory control. This model is a good example of our profession, as it demonstrates the state-of-the-art in contemporary industrial engineering paradigms (see, for example, [7, 8]). The mathematical model is studied under various objective functions, while the models and the implications of the solutions were discussed with the plant managers. The model itself is a contribution of this study, as it combines several operations management models, hitherto handles separately, into a single formulation.
There are a finite number of meaningful formulations, since we are limited to integer programming models with a finite number of variables. In another words, as there are limited numbers of transporters, parts, stations, and epochs. In principle, all possible assignments may be evaluated for their suitability. In effect, if there is a suitable model formulation, the approach is guaranteed to uncover it. However, none of the solutions to the simplified model were deemed to satisfy the plant managers and their expectations from Industry 4.0. Consequently, the study serves as a counterexample, indicating that if Industry 4.0 practices of high-level integration and optimization are to be achieving, a rethink of industrial engineering practices is in order. This qualitative finding is most significant contribution of this study. Finally, we offer concluding remarks based on our experiences and directions for future work.

2. Materials handling operations

Recent work at an assembly plant, whose managers are keen to be early implementers of Industry 4.0 practices, provides the basis of our discussions. The system is characterized by well-tuned operations along relatively long assembly lines, where station operations are balanced, and where the materials are fed in a manner that minimizes inventory along assembly stations. A good example is the assembly of automotive harnesses.
The complexity of the assembly process is due to the large number of small parts that must be delivered to the stations at regular intervals. Not only that the right parts need to be delivered, but also there is a need to keep the assembly areas free of clutter. Moreover, as customization increases and batch sizes decrease, frequent product changes are to be expected. Hence, keeping minimum stock on the assembly floor positively affects agility and rapid reconfigurability. Materials handling is done by (human or robotic) transporters who pick boxes of parts at a central warehouse and deliver them to the assembly stations following a regular path (see Fig. 2). Currently, a Kanban system is used where empty boxes are indicated by *cards*. The cards may be traditional paper or electronic RFID-type records. The transporter accumulates the Kanban cards from the empty bins. New parts are delivered to the bins whose Kanban cards were collected during the previous round. The time it takes the transporters to make their round is considered as one epoch. Typically, each box contains enough parts to feed the assembly station for at least one epoch. In the typical cases, at most two epoch's worth of supplies is present at the station-side inventory, preferably as two boxes. When one is empty, it is to be replaced within time, while the second box is being used. For some `high-demand' components, multiple boxes may be delivered per epoch. A two-way `supplies corridor' is constructed, along which transporters run, stopping at the stations. Upon delivery completion, the transporter returns to the main warehouse along the same corridor (see Fig. 2).

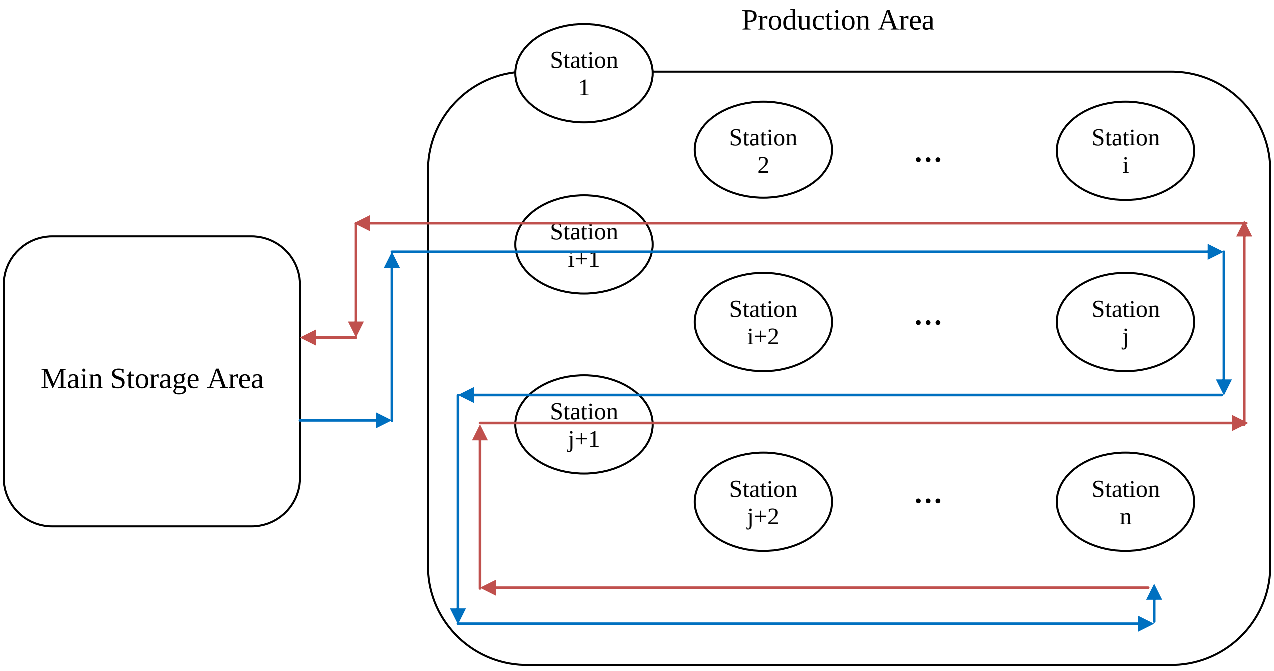

Figure 2. Transporter's route

3. Literature review

Our setting combines components from different domains such as Kanban systems, materials handling and Industry 4.0. Kanban systems, introduced by Sugimori et al. [9], is based on the procurement of the right amount of the required material at the exact right time so as to achieve a reduction of cost through the elimination of waste and excess inventory. Since then, this approach has received much attention and has been adopted by considerably many manufacturers. The main focus is on parameter estimation of a Kanban system such as the Kanban size, the number of Kanbans, scheduling policies, etc. [10, 11, 12]. There are also comprehensive literature surveys on Kanban systems [13, 14]. These provide a broad exposure to Kanban systems and to the classification techniques for the design and operational issues. Importantly, Huang and Kusiak [14] pointed out that the Kanban system is not a panacea for all industrial problems. This system is convenient only if different factors such as lot sizes, workforce flexibility, and set-up times are jointly planned.

Another research stream, the determination of the number of vehicles in a material transport system gained importance in the 1980s with the rise of automatic guided vehicles (AGVs). One task is estimating the number of AGVs for the transportation of the materials using different techniques such as queuing-theory based, simulation-based, and analytical techniques [15, 16]. Another task is the minimization of the fixed and operational costs of the material handling system by deploying a minimum number of transporters and seeking the minimum handling effort. Integer programming models and heuristics have been developed [17, 18]. Our approach is to integrate materials handling operations with a Kanban system so that management can achieve its targets under different scenarios.

Some background on Industry 4.0 was given in the very first section. The literature shows a growing interest in the implementation of industrial engineering tools to Industry 4.0 [19, 20]. For instance, some study the impact of 'Lean Production' on 'Industry 4.0' [21, 22]. Furthermore, the review article of Liao et al. [23] gives a detailed analysis of academic progress in Industry 4.0 and provides potential future research directions. Nevertheless, recent research also includes hints that the application existing tools to Industry 4.0

are not necessarily straightforward. Interestingly, findings contrary to intuition and general opinion, implies human involvement may actually increase in smart facilities. However, the role of the workers will be at a higher intellectual level and be more demanding in terms of skills and specialization [24, 25, 26].

Kanban and materials handling systems have been evolving and maturing over time. However, as Industry 4.0 seems to indicate, there remains a need to bridge these two areas, as tactical and operational decisions are made. Our study is an attempt in this direction. Our purpose is also to show that, similar to the conclusion of Huang and Kusiak [14], an immediate integration of Kanban and materials handling systems does not necessarily satisfy the ambitions of Industry 4.0. Moreover, we aim to point out that there is still a need for human decision-making, or at least, for fine-tuning the results of industrial engineering tools.

4. Company desiderata and model properties

The company desiderata is given as, (1) minimize the number of transporters, (2) maximize transporter utilization, (3) keep the number of transporters constant throughout production, (4) keep no more than one epoch's worth of additional (safety stock) station-side inventories. Following the best practices of industrial engineering and operations research, a mixed-integer optimization model is developed. The model is presented in detail in the following section.

As further motivation and justification, we note that the model is an interesting one, which integrates elements of the assignment problem, the knapsack problem, the bin packing problem, the vehicle routing problem, and inventory control. If the box sizes vary a lot and the limiting factor is the capacity of the transporter carts, then loading the carts becomes the overwhelming concern. This becomes a knapsack problem for each transporter at the beginning of each epoch. On the other hand, the parts replenishment operation at the stations may be considered as a version of the bin packing problem. Of course, the delegation of jobs to the transporters is an assignment problem, while viewing the system as a set of station-side intermediate stocks; we are confronted by an inventory problem. Managerial experience shows that designing a robust and efficient parts replenishment system is a rather convoluted proposition.

Management would like the model to be integrated into the IT backbone, so that it can be run in real time. That is, management would like it if there were no hesitation to quickly change over the setups, driven by spur-of-the-moment opportunities. This desire follows directly from the promises of Industry 4.0. Moreover, management not only demands a reliable, integrated, and robust solution, but also desires the solution to be intuitive and meaningful. In this respect, combining the competing objectives with simple linear weights was deemed unacceptable. In addition, management views the solution provided by the optimization model as a starting point, from which alterations could be made. For instance, management considers it acceptable to occasionally allow a transporter utilization factor greater than unity in order to force a better solution. Accordingly, of the four demands listed above, we experiment with various objectives and constraints.

5. Mathematical model

We construct a mixed-integer programming model whose solution would give us an optimum assignment of supply boxes to the transporters for each epoch. The model is developed as a general model, while we will entertain various ideas concerning the objective and the constraints. The decision variables are denoted by capital letters and the parameters (except for the traditional *big M*) by lower-case letters, as given in Table 1. The model is presented in a form that enhances clarity. Most importantly, decision variables include several auxiliary variables (functions of the primary decision variables) as further discussed below.

Table 1. Notation

Sets		
n	Part types	$n \in \{1, 2, \ldots, N\}$
j	Stations	$j \in \{1, 2, \ldots, J\}$
k	Transporters	$k \in \{1, 2, \ldots, K\}$
t	Epochs	$t \in \{1, 2, \ldots, T\}$
Parameters		
h_n	Size of part type n	$\forall n$
p_j	Travel time up between station j-1 and j	$\forall j$
b_n	Box handling time of part type n	$\forall n$
d_{nj}	Demand of part type n for station j per epoch	$\forall n$, $\forall j$
c	Capacity of the transporter	
M	Big M value	
w	Workload	
y	Maximum station-side inventory left at the end of all except the last epoch	
l	Maximum station-side inventory left at the end of the last epoch	
Primary Decision Variables		
S_{njkt}	Number of part type n boxes carried by transporter k to station j in epoch t	$\forall n, \forall j, \forall k, \forall t$
Derivative Decision Variables		
I_{njt}	Inventory level of part type n in station j at the beginning of epoch t	$\forall n, \forall j, \forall t$
V_{jkt}	Binary variable, takes 1 if transporter k visits station j in epoch t	$\forall j, \forall k, \forall t$
U_{kt}	Binary variable, takes 1 if transporter k is used in epoch t	$\forall k, \forall t$
B_{kt}	Total box handling time for transporter k in epoch t	$\forall k, \forall t$
R_{kt}	Travel time of transporter k (Round trip)	$\forall k, \forall t$
Q_t	Number of transporter used in epoch t	$\forall t$

Time is measured in epochs, i.e., one epoch is one time unit. The parts are measured in box units or load units. This unit is used for the demand and for the transport cart capacity. The following model is the basis for all derivative formulations considered.

There are six different forms of the objective function F, four of which are given below, and the remaining two, a little later. Constraint (1) sets the transporter capacity. Constraint (2) defines the box handling times. Note that the workload of transporters consists of travel time and the box handling time which is later expressed by constraint (7). Constraints (3) and (4) set the binary variables V_{jkt} to 1 if there is a delivery to station j by transporter k during epoch t, and set its value to 0 otherwise. Note that the variables S_{njkt} denote the number of boxes, and thus are integers. The Big M value is needed in constraint (3), since the variables V_{jkt} are binary (at most 1). Here the value of Big M need not be very larger (only as large as the maximum number of boxes deliverable to the stations). Constraint (5) ensures that if a transporter visits a station during an epoch, the transporter travels past its predecessor station along the route. Travel times p_j are expressed in an incremental manner. Thus, the time it takes for a round trip to a station is computed as the sum of all incremental travel times up to that station. Equation (6) accomplishes this. The next four constraints (8), (9), (10), and (11) specify the initial and final inventory levels, and relate the inventory levels between successive epochs. We take the final inventory to be no more than a single box
(l=1). The final four constraints (12), (13), (14), and (15) set the nonnegativity and integrality conditions.

optimize F

subject to:

$$\sum_{n,j} h_n \cdot S_{njkt} \leq c, \qquad \forall k, \forall t. \tag{1}$$

$$\sum_{n,j} b_n \cdot S_{njkt} = B_{kt}, \qquad \forall k, \forall t. \tag{2}$$

$$\sum_{n} S_{njkt} \leq M \cdot V_{jkt}, \qquad \forall j, \forall k, \forall t. \tag{3}$$

$$\sum_{n,i:i\geq j} S_{nikt} \geq V_{jkt}, \qquad \forall j, \forall k, \forall t. \tag{4}$$

$$V_{(j-1)kt} \geq V_{jkt}, \qquad \forall j > 1, \forall k, \forall t. \tag{5}$$

$$\sum_{j} p_j \cdot V_{jkt} = R_{kt}, \qquad \forall k, \forall t. \tag{6}$$

$$B_{kt} + R_{kt} \leq w, \qquad \forall k, \forall t. \tag{7}$$

$$I_{nj(t+1)} = I_{njt} + \left(\sum_{k} S_{njkt}\right) - d_{nj}, \qquad \forall n, \forall j, \forall t < T. \tag{8}$$

$$I_{nj1} = 0, \qquad \forall n, \forall j. \tag{9}$$

$$I_{njT} \leq l, \qquad \forall n, \forall j. \tag{10}$$

$$I_{njt} \leq y, \qquad \forall n, \forall j, \forall t. \tag{11}$$

$$S_{njkt} \geq 0, \quad \text{integer}, \qquad \forall n, \forall j, \forall k, \forall t. \tag{12}$$

$$I_{njt} \geq 0, \qquad \forall n, \forall j, \forall t. \tag{13}$$

$$B_{kt}, R_{kt} \geq 0, \qquad \forall k, \forall t. \tag{14}$$

$$V_{jkt} \in \{0, 1\}, \qquad \forall j, \forall k, \forall t. \tag{15}$$

As stated, the formulation is written for clarity rather than brevity. It is possible to reduce the number of decision variables and constraints. For example, (2) could be dispensed of and inserted directly into (7). In this sense, the decision variables B_{kt} are derivatives of the primary decision variables S_{njkt}. Other derivative decision variables are similarly related to the primary decision variables. We keep the current formulation, since modern optimization software would already simplify and normalize the constraint set before initiating the computations.

Note that the primary decision variables are bounded nonnegative integers. That is, the number of part type *n* boxes carried by transporter *k* to station *j* in epoch *t* is an integer. The upper bounds follow from the fact that demand is finite. There is no need to transport more than the demand to the stations. Consequently, the decision variable space consists of a finite number of discrete solutions. This observation guarantees that the flowchart depicted by Fig. 1 is guaranteed to find a suitable model, provided that one exists, or else will terminate with the conclusion that no satisfactory model is possible. Conceptually, this constitutes the fundamental issue addressed by this study. We initially consider and experiment with four objective functions:

1. If we would like to minimize the maximum number of transporters per shift, we need to add the following constraints to the model.

$$maximize\ F_1$$

$$M.U_{kt} \geq \sum_{n,j} S_{njkt}, \qquad \forall k, \forall t. \tag{16}$$

$$Q_t = \sum_{k} U_{kt}, \qquad \forall t. \tag{17}$$

$$F_1 \geq Q_t, \qquad \forall t. \tag{18}$$

$$U_{kt} \in \{0,1\}, \qquad \forall k, \forall t. \tag{19}$$

Here, the binary variables U_{kt} are set to 1 if transporter k is used during epoch t, and set to 0 otherwise. Q_t then becomes the total number of transporters used during epoch t, and F is the maximum number of transporters used in any epoch.

2. If we prefer to minimize the total number of transporter round-trips during a shift, we keep the constraints (16), (17), and (19) but define the objective function as

$$maximize\ F_2 = \sum_{t} Q_t. \tag{20}$$

3. Similarly, in order to maximize the minimum transporter workload during a shift, we use

$$maximize\ F_3$$

$$F_3 \leq\ B_{kt} + R_{kt} + M.(1 - U_{kt}), \qquad \forall k, \forall t. \tag{21}$$

Here, we ignore the epochs unless a transporter is actually used. The binary variable U_{kt} is 0 if the transporter is not used, and hence, the inequality is automatically satisfied.

4. Finally, we consider maximizing the total transporter workload during a shift.

$$maximize\ F_4$$

$$F_4 \leq \sum_{k,t} (B_{kt} + R_{kt}). \tag{22}$$

In order to address the four concurrent demands of management as listed above, we experiment with these four objective functions. Two mainly focus on the minimization of the number of transporters (F_1 and F_2) and the remainder, the maximization of the workloads of the transporters (F_3 and F_4). In the next section, we interpret the results of a simple example.

6. Results and insights

The computations were carried out using CPLEX. As the problem is most likely NP-complete, any deployment of the methodology would undoubtedly require heuristics to be developed. However, before any deployment, we examine the solutions for a simple example to gain insights.

In the example, there are five types of parts, to be delivered to five stations, during a shift of five epochs. The initial inventory is assumed to be empty. The maximum allowed inventory is two boxes. The transport cart has a capacity of 100 box units. The size of the parts boxes are 10, 20, 5, 10, and 5, respectively. The additional travel time (measured in epochs) incurred for the five stations are 0.20, 0.10, 0.15, 0.10, and 0.10. Similarly, the box handling times for the five types of parts 0.02, 0.07, 0.05, 0.03, and 0.05. The demand is given in box units for each epoch in Table 2.

Table 2. Demand of parts at stations for each epoch

Part	Station				
	1	2	3	4	5
1	0.7	0.2	0.5	0.9	0.5
2	0.5	0.4	0.5	0.1	0.6
3	0.5	0.6	0.5	0.7	0.5
4	0.5	0.2	0.5	0.3	0.5
5	0.8	0.2	0.5	0.8	0.5

6.1. Preliminary results

The data is such that transporter capacities are not binding constraints. However, it is difficult to maintain low inventories while keeping the number of transporters down. A complete set of problems were constructed and solved to optimality using each objective function given in the section above. Each problem in the set specifies a different number of transporters (K=1,2,3,4,5), for each epoch (T=1,2,3,4,5). In addition, we relax the requirement that we keep as little safety stock as possible. Towards this end, we allow different values of the parameter y (y=1,2,3,4), which denotes the maximum allowed inventory. Table 3 shows the maximum, average, and minimum workloads of the transporters for different Kanban levels under different objectives for a fixed number of transporters in each epoch. (K=1, 2 are skipped since at least three transporters are needed to deliver the parts).

Table 3. Transporter Workloads (constant number of transporters per epoch)

Objective	*K*	*y*			
		1	2	3	4
F_1	3	(1.00, 0.82, 0.52)	(1.00, 0.63, 0.24)	(1.00, 0.58, 0.22)	(1.00, 0.57, 0.22)
	4	(1.00, 0.78, 0.55)	(1.00, 0.74, 0.25)	(1.00, 0.76, 0.23)	(1.00, 0.60, 0.22)
	5	(1.00, 0.77, 0.42)	(0.99, 0.65, 0.22)	(1.00, 0.63, 0.22)	(0.97, 0.61, 0.22)
F_2	3	(1.00, 0.86, 0.72)	(0.99, 0.58, 0.25)	(0.99, 0.67, 0.25)	(0.99, 0.63, 0.25)
	4	(0.99, 0.78, 0.40)	(1.00, 0.76, 0.27)	(1.00, 0.76, 0.27)	(1.00, 0.76, 0.27)
	5	(1.00, 0.74, 0.25)	(1.00, 0.68, 0.25)	(1.00, 0.67, 0.25)	(1.00, 0.66, 0.25)
F_3	3	(1.00, 0.88, 0.81)	(0.99, 0.88, 0.84)	(0.99, 0.88, 0.84)	(1.00, 0.88, 0.84)
	4	(1.00, 0.84, 0.74)	(1.00, 0.81, 0.78)	(0.99, 0.83, 0.78)	(0.97, 0.81, 0.78)
	5	(1.00, 0.80, 0.65)	(0.94, 0.76, 0.69)	(0.92, 0.76, 0.69)	(0.99, 0.76, 0.69)
F_4	3	(1.00, 0.91, 0.72)	(1.00, 0.91, 0.70)	(1.00, 0.91, 0.68)	(1.00, 0.91, 0.67)
	4	(1.00, 0.85, 0.67)	(1.00, 0.79, 0.27)	(1.00, 0.79, 0.27)	(1.00, 0.79, 0.27)
	5	(1.00, 0.82, 0.60)	(1.00, 0.82, 0.60)	(1.00, 0.82, 0.60)	(1.00, 0.82, 0.60)

Next, we relax the constraint that the number of transporters in each epoch is constant. The results in Table 4 show the number of transporters required in each epoch and the maximum, average, and minimum workloads of the transporters for different Kanban levels under different objectives. F_4 is excluded from Table 4 since it repeats a previous case using all transporters.

Table 4. Transporter Workloads (variable number of transporters per epoch)

Objective	*y*	*Number of transporters in epochs*	*Workloads (Max, Average, Min)*
F_1	1	(3, 2, 3, 1, 0)	(1.00, 0.89, 0.60)
	2	(3, 2, 3, 3, 0)	(1.00, 0.78, 0.25)
	3	(3, 2, 2, 1, 0)	(1.00, 0.92, 0.78)
	4	(3, 2, 3, 2, 0)	(1.00, 0.75, 0.25)
F_2	1	(3, 2, 1, 1, 0)	(1.00, 0.87, 0.86)
	2	(4, 1, 1, 0, 0)	(1.00, 0.99, 0.98)
	3	(4, 0, 1, 1, 0)	(1.00, 0.95, 0.83)
	4	(5, 1, 0, 0, 0)	(1.00, 0.99, 0.96)
F_3	1	(3, 1, 2, 1, 0)	(0.99, 0.97, 0.94)
	2	(4, 1, 2, 0, 0)	(1.00, 0.99, 0.98)
	3	(4, 1, 2, 0, 0)	(1.00, 0.99, 0.98)
	4	(3, 3, 1, 0, 0)	(1.00, 0.99, 0.99)

As we gain insights into the structure of the system and its resultant behaviour, we come to the understanding that any regulation of transporter operations must alter some of the basic premises of the operating policies. The most obvious one is the relaxation of the Kanban policy. If we allow larger inventories than the minimum dictated by lean manufacturing principles, it seems plausible that transporter operations may be further streamlined. In this sense, there is a fundamental trade-off between 'lean manufacturing' and 'as lean as possible but not any leaner than that' manufacturing.

None of the solutions was deemed satisfactory by management. Even for this small problem, no solution fulfills the desiderata. For instance, when the model is run requiring the same number of transporters at each epoch, and with the objective of minimizing the maximum number of transporters per shift, the best solution requires three (3) transporters, with a minimum workload of 0.24, an average workload of 0.63. Fig. 3 shows the distribution of transporter workloads.

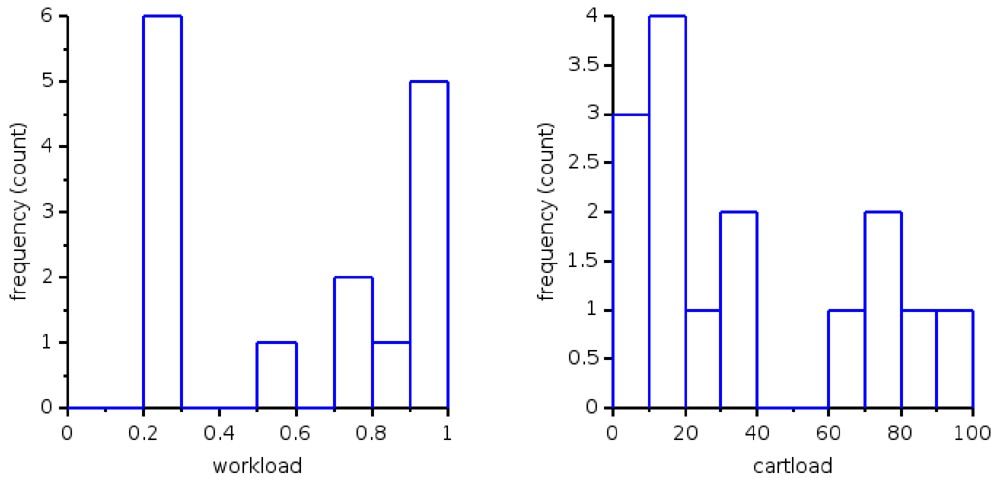

Figure 3. Workload and cartload distribution, Case: minimize the maximum number of transporters, same number of transports at each epoch, Cart capacity=100, Number of transporters=3

Clearly, management considers a minimum workload of 24% to be unacceptably poor. Moreover, the transport carts seem to be exceedingly underutilized. With a capacity of 100, cart loads range from 5 to 40 for 75% of the transports.

If we relax the requirement that all epochs must have the same number of transporters, then the minimum workload of 0.25 is obtained with 3, 2, 3, 3, and 0 transporters being used. Here, 11 transporters are used during the shift, compared to the 15 when transporter numbers were to be unchanged. The minimum workload of 25% is unacceptable (see Fig. 4). The average workload is 0.78 with a standard deviation of 0.22. Both of these performance measures are an improvement over the previous constant-number-of-transporters case. However, varying number of transporters (0 to 3) during the shift is unacceptable. Again, the cart loads between 5 and 95 are quite low.

If we reduce the cart capacity to 80, forcing this solution to be infeasible, and insist that the number of transporters remain the same throughout the shift, we need 4 transporters. The solution becomes even less attractive to management. Just because a single epoch requires a little more cart space, we are forced to increase the number of transporters.

We observe that minimizing the maximum number of transporters (F_2) is of little use. There seem to be some epochs during which many inventories happen to be depleted around the same time. These critical epochs require a large number of transporters. Minimizing of the maximum number of transporters allows the assignments during the non-critical epochs to be rather relaxed, resulting in inefficiencies indicated by low workloads. The plant envisions implementing automated robotic transports. A low utility translates to difficulties in justifying investments into the automated systems.

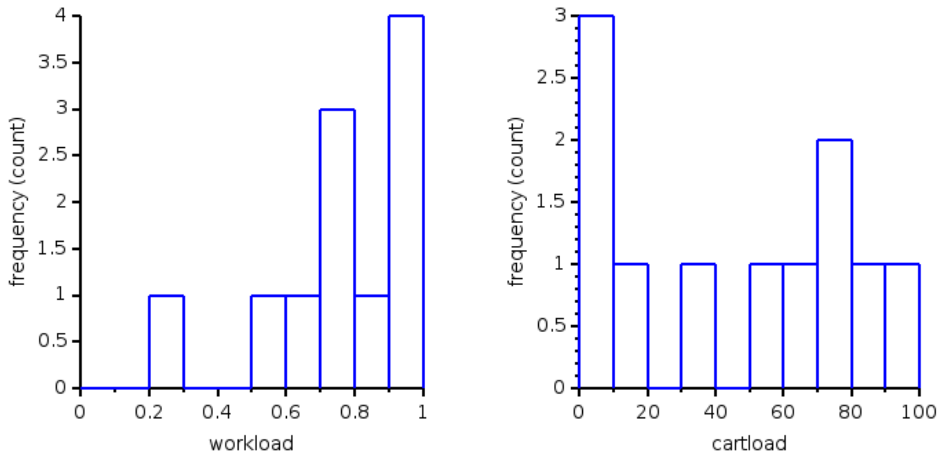

Figure 4. Workload and cartload distribution, Case: minimize the maximum number of transporters, Cart capacity=100, Number of transporters in each epoch=(3,2,3,3,0)

A better objective seems to be the minimization of the total number of transporter round-trips during a shift (F_1). This approach acknowledges that there will be peaks in replenishment jobs during the shift, as well as periods of relative lull. Management would be happier with assignments where each epoch has the same number of transporters. Otherwise, transporters must be given alternate tasks during the less intensive epochs. Again, this would be problematic in the case of robotic transports.

6.2. Modified objective functions

Maximizing transporter workloads (F_3 and F_4) leads to some of the idiosyncrasies in almost all cases. The optimization solution attempts to artificially inflate the transporter workloads by assigning at least one delivery towards the end of the line. This leads to increasing the travel times for all transporters, and thus a higher workload. However, it is quite undesirable to increase unnecessary travel time just to increase the workload. It is best to assign the jobs so that as many of the transporters finish the deliveries and return to the main warehouse as soon as possible. In order to overcome this idiosyncrasy, we employ two new objective functions.

Instead of maximizing total workload, we maximize the minimum transporter value-added (box handling time) workload during a shift. Accordingly, modifying F_3, we have,

$$\begin{aligned} &maximize\ F_5 \\ &F_5 \leq B_{kt} + M.(1 - U_{kt}), \qquad \forall k, \forall t. \end{aligned} \tag{23}$$

Here, we consider only the box handling times of the transporter. In the next objective function, we maximize the total transporter value-added workload during a shift, which again only considers box handling times of the transporter.
This objective function is a modification of F_4.

$$\begin{aligned} &maximize\ F_6 \\ &F_6 = \sum_{k,t} B_{kt}. \end{aligned} \tag{24}$$

Table 5. Transporter Workloads (box handling times only, constant number of transporters per epoch)

Objective	*K*	*y*			
		1	2	3	4
F_5	3	(1.00, 0.77, 0.40)	(1.00, 0.86, 0.66)	(0.99, 0.71, 0.40)	(1.00, 0.73, 0.40)
	4	(0.96, 0.66, 0.34)	(1.00, 0.72, 0.36)	(1.00, 0.74, 0.35)	(0.97, 0.71, 0.35)
	5	(0.99, 0.53, 0.30)	(0.99, 0.55, 0.32)	(0.94, 0.65, 0.32)	(0.97, 0.59, 0.32)
F_6	3	(1.00, 0.90, 0.72)	(1.00, 0.75, 0.25)	(1.00, 0.77, 0.25)	(1.00, 0.72, 0.25)
	4	(1.00, 0.83, 0.53)	(1.00, 0.79, 0.27)	(1.00, 0.79, 0.27)	(1.00, 0.79, 0.27)
	5	(1.00, 0.77, 0.22)	(1.00, 0.73, 0.25)	(1.00, 0.71, 0.25)	(1.00, 0.70, 0.25)

Table 5 presents the maximum, average, and minimum workloads of the transporters for different Kanban levels under objectives F_5 and F_6. When we compare the workloads given in Table 3 (F_3 and F_4) to Table 5 (F_5 and F_6), we see that the workloads declined in general as the model no longer tries to send the transporter to the end of the line. These workloads are still much lower than managerially acceptable.
We also relax the constraint that the number of transporters remains constant (F_5). Table 6 presents the number of transporters required in each epoch and the maximum, average, and minimum workloads of the transporters for different Kanban levels for maximizing the minimum transporter value-added workload during a shift. Again, the workloads tend to decline, especially those with a low utilization value. F_6 is excluded in Table 6 since it uses all the transporters in all epochs.

Table 6. Transporter Workloads (box handling times only, variable number of transporters per epoch)

Objective	*y*	*Number of transporters in epochs*	*Workloads (Max, Average, Min)*
F_5	1	(3, 2, 1, 2, 0)	(0.99, 0.94, 0.79)
	2	(4, 1, 2, 0, 0)	(1.00, 0.92, 0.57)
	3	(4, 1, 2, 0, 0)	(1.00, 0.93, 0.67)
	4	(4, 2, 1, 1, 0)	(1.00, 0.91, 0.59)

Fulfilling managerial desiderata in its totality is a rather unrealistic expectation. Here, we have a good example of the systems aspects of complex production lines. Simply changing one aspect of a complex system usually affects many other unintended and undesirable aspects.

7. Conclusions and future directions

Based on recent work at a manufacturing plant whose managers would like to initiate a pilot program towards Industry 4.0, we present a mixed-integer optimization formulation of a materials handling system. The model integrates inventory, knapsack, transporter assignment, vehicle routing, and bin packing aspects of the materials handling system. As far as we know, this is the first study of its kind to present such level of integration. As a first step, the model was run with realistic data on a small scale, and optimal solutions were presented to management.

There are a few rather tactical extensions to this work, two of which are under investigation. First, if the model is to be solved for realistic cases, heuristics must be developed to tackle the computational complexity. Second, the current linear arrangement is to be extended to other network topologies beyond a simple corridor.

As for the more strategic directions, we observe that none of the solutions to the simple example being acceptable to management has significant implications to the limits to large-scale optimization envisioned in Industry 4.0. Only one study is insufficient to decisively declare that industrial engineering paradigms need a rethink for Industry 4.0. After all, this is a rather strong statement with far-reaching implications. The present work nonetheless provides at least an example where this is not the case. As such, it gives rise to a hypothesis and justifies further investigation into the matter.

If indeed current industrial engineering paradigms fall short of satisfying Industry 4.0 objectives, there may be several future avenues of progress towards a remedy. We close by listing four such future scenarios, each pointing to a longer term research direction.

7.1. Future directions

Expanding the model scope

Even though we fail to fulfill the given desiderata, we note that not all operational parameters have been subject to adjustment. It may be possible to reach satisfactory solutions if the scope of the optimization effort were to be expanded. For example, we may allow the length of the epochs to be a decision variable. Similarly, we may consider the length of the shifts to be chosen to aid “optimality”. Again, we may allow the cart capacities to be subject to design. In principle, starting with a clean slate and picking the operational parameters from scratch has a potential to deliver sufficiently desirable solutions. Rather than standing in contrast to Industry 4.0 principles, this scenario would be further motivation to expand the scope of integration. We leave this investigation to a future study.

Embedding mathematical optimization into the artificial intelligence backbone

Although mathematical programming does not necessarily give us ideal solutions, nonetheless, management finds intuitive value in the set of provided solutions. A good operations manager finds hints as to where the trade-offs should be made, and obtains a `best schedule' from the provided information. Here, it is suspected that the decision maker first eliminates the readily inappropriate (or infeasible) solutions, and then, considers good compromises to make the best of what is at hand. In either case, Industry 4.0, with its emphasis on advanced information technologies, may lead to an artificial intelligence (AI) approach. Industrial engineering has in the past experimented with some crude AI approaches, such as ‘expert systems’ [27]. Industry 4.0 may expand and extend this approach. In this scenario, mathematical optimization provides yet another set of real-time information, but where the decision making is conducted by the AI layer of the system, not by the optimization engine.

Reducing the emphasis on optimality

One view of the future where Industry 4.0 is implemented hints at large-scale optimization which recognizes that operating policies will not be as close to their stand-alone optimal settings. In other words, global large-scale system optimality may be consigned to a less pronounced priority. In our case, for instance, the requirement that all epochs use the same number of transporters may be depreciated. If automated transporters are used, this means investments may be justified even though workloads are typically lower than desired. This scenario gains credence as we observe that technology swiftly becomes cheaper over time.

Manufacturing is a complex system

A prominent view in literature [28, 29, 30] submits that unlike simple conglomerates, a manufacturing plant is to be viewed as a complex system. As such, a high level of redundancy is to be expected to achieve the desired levels of intelligence and robustness. After all, naturally occurring systems, such as biological systems, are endowed with multitudes of redundancy (e.g., the DNA). Even complex artificial systems, such as the Internet or modern operating systems, maintain a high level of redundancy. Thus, the view of insisting on unconditional optimality is to be discarded in favor of complexity gains traction. This has profound implications on traditional industrial engineering practices, where hitherto the major emphasis has been on analytical methods to achieve optimality. Industry 4.0 may force a review of this practice, and hence, may offer to be a useful catalyst in shaping the future of industrial engineering.

References

[1] D. Kolberg and D. Zühlke, Lean automation enabled by industry 4.0 technologies, IFAC-PapersOnLine, vol. 48 (3), pp. 1870 – 1875, 2015.

[2] H. Kagermann, W. Wahlster and J. Helbig, Recommendations for implementing the strategic initiative industrie 4.0, Tech. rep., German National Academy of Science and Engineering , April 2013.

[3] M. Hermann, T. Pentek and B. Otto, Design principles for industrie 4.0 scenarios, in: System Sciences (HICSS), 49th Hawaii International Conference on, IEEE, pp. 3928-3937, 2016.

[4] H. Kim, S. Kim, J. Deng, J.-L. Lu, K. Wang, C. Zhang, M. A. Grover and B. Wang, An integrated holistic model of a complex process, International Journal of Advanced Manufacturing Technology, vol. 89 (1-4), pp. 1137-1147, March 2017.

[5] C. Baur and D. Wee, Manufacturings next act (June 2015). URL http://www.mckinsey.com/business-functions/operations/our-insights/manufacturings-next-act

[6] M. Breunig, R. Kelly, R. Mathis and D. Wee, Getting the most out of industry 4.0 (April 2016). URL http://www.mckinsey.com/business-functions/operations/our-insights/industry-40-looking-beyond-the-initial-hype

[7] L. A. Johnson and D. C. Montgomery, Operations Research in Production Planning, Scheduling, and Inventory Control, John Wiley & Sons, Inc., "Hoboken, New Jersey", 1974.

[8] E. Silver, D. Pyke and R. Peterson, Inventory Management and Production Planning and Scheduling, Wiley, 1998.

[9] Y. Sugimori, K. Kusunoki, F. Cho and S. Uchikawa, Toyota production system and kanban system materialization of just-in-time and respect-for-human system, The International Journal of Production Research, vol. 15 (6), pp. 553-564, 1977.

[10] F. Erhun, M. S. Akturk and A. Turkcan, Interaction of design and operational parameters in periodic review kanban systems, International Journal of Production Research, vol. 41 (14), pp. 3315-3338, 2003.

[11] T. Murino, G. Naviglio, E. Romano and P. Zoppoli, Single stage multi product kanban system. Optimization and parametric analysis, in: Proceedings of the 8th WSEAS International Conference on System Science and Simulation in Engineering, Genova, Italy, pp. 313-319, 2009.

[12] R. Piplani and A. W. H. Ang, Performance comparison of multiple product kanban control systems, International Journal of Production Research, 56:3, 1299-1312, 2018.

[13] M. S. Akturk and F. Erhun, An overview of design and operational issues of kanban systems, International Journal of Production Research, vol. 37 (17), pp. 3859-3881, 1999.

[14] C. Huang and A. Kusiak, Overview of kanban systems, International Journal of Computer Integrated Manufacturing, vol. 9 (3), pp. 169-189, 1996.

[15] P. J. Egbelu, The use of non-simulation approaches in estimating vehicle requirements in an automated guided vehicle based transport system, Material Flow, vol. 4 (1), pp. 17-32, 1987.

[16] J. Tanchoco, P. Egbelu and F. Taghaboni, Determination of the total number of vehicles in an AGV-based material transport system, Material Flow, vol. 4 (1-2), pp. 33-51, 1987.

[17] J. W. Herrmann, G. Ioannou, I.Minis and J. Proth, Minimization of acquisition and operational costs in horizontal material handling system design, IIE transactions, vol. 31 (7), pp. 679-693, 1999.

[18] G. Ioannou and M. N. Kritikos, Optimization of material handling in production and warehousing facilities, Operational Research, vol. 4 (3), pp. 317-331, 2004.

[19] D. Ivanov, A. Dolgui, B. Sokolov, F. Werner and M. Ivanova, A dynamic model and an algorithm for short-term supply chain scheduling in the smart factory industry 4.0, International Journal of Production Research, vol. 54 (2), pp. 386-402, 2016.

[20] G. L. Tortorella and D. Fettermann, Implementation of industry 4.0 and lean production in Brazilian manufacturing companies, International Journal of Production Research, vol. 56 (8), pp. 2975-2987, 2018.

[21] B. Mrugalska and M. K. Wyrwicka, Towards lean production in industry 4.0, Procedia Engineering, vol. 182, pp. 466-473, 2017.

[22] T. Wagner, C. Herrmann and S. Thiede, Industry 4.0 impacts on lean production systems, Procedia CIRP, vol. 63, pp. 125-131, 2017.

[23] Y. Liao, F. Deschamps, E. de Freitas Rocha Loures and L. F. P. Ramos, Past, present and future of industry 4.0 - a systematic literature review and research agenda proposal, International Journal of Production Research, vol. 55 (12), 3609-3629, 2017.

[24] B. Dworschak and H. Zaiser, Competences for cyber-physical systems in manufacturing-First findings and scenarios, Procedia CIRP, vol. 25, pp. 345- 350, 2014.

[25] D. Kolberg, J. Knobloch and D. Zühlke, Towards a lean automation interface for workstations, International Journal of Production Research, vol. 55 (10), pp. 2845-2856, 2017.

[26] A. Sanders, C. Elangeswaran and J. Wulfsberg, Industry 4.0 implies lean manufacturing: Research activities in industry 4.0 function as enablers for lean manufacturing, Journal of Industrial Engineering and Management, vol. 9 (3), pp. 811-833, 2016.

[27] S. H. Liao, Expert system methodologies and applications-a decade review from 1995 to 2004, Expert systems with applications, vol. 28(1), pp. 93-103, 2005.

[28] R. L. Acko, Re-Creating the Corporation: A Design of Organizations for the 21st Century, Oxford University Press, Oxford, UK, 1999.

[29] J. Boardman and B. Sauser, Systems Thinking: Coping with 21st Century Problems, CRC Press, Boca Raton, Florida, 2008.

[30] P. Checkland, Systems Thinking, Systems Practice: Includes a 30-Year Retrospective, John Wiley & Sons, Inc., "Hoboken, New Jersey", 1999.